# Advances in state-space modeling using time-base filtered predictors

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**Abstract**

Time base difference technique is introduced in filtering the exogenous variable into two indicative predictor variables in state space model framework for examining the sensitivity of the observed variable to dimensional changes in the predictor variable. Estimation is based on Kalman filter and Aikaike information criterion (AIC) was adopted to select the more preferred model. The empirical application indicates that AIC preferred the state space model with time- base filtered predictors to the one without time-base filtered predictors. The procedure offers a unique mode of filtering a quantitative data into two-dimensional data sub-sets for sensitivity study.

**Key words:** Time-Base Difference Technique, Filtered Predictor, AIC, State-Space Model

**JEL Classification: C01, C32, E52**

## Introduction

State-space models have been broadly applied to study macroeconomic and financial problems. For example, they have been applied to model unobserved trends, to model transition from one economic structure to another, to forecasting models, to study wage-rate behaviors, and to model time-varying monetary reaction functions. One of the earliest application of state space modeling is that of Fama and Gibbons (1982), who modeled the unobserved ex-ante real interest rate as a state variable that follows an AR(1) process using Kalman Filter. Stock and Watson (1991) work was another important contribution that defined an unobserved variable, which represents the state of business cycle, to measure the common element of co-movements in various macroeconomic variables.

The present paper examines the situation where the exogenous (explanatory) variable in the observation equation can be filtered into two indicator variables using a proposed technique called time-base difference (percentage relative change between a base-time observation $(X_1)$ and successive observations $(X_{t+i})$. The essence of decomposition of the explanatory variable into two independent indicator variables using time-base difference, are as follows; firstly, it integrates dimension into explaining observable factors when there is a control variable that is not stable over-time. It helps to filter out the sensitivity of the observed (explained) variable in the measurement equation to dimensional changes in the control (predictor) variable. For instance, economic state of a country may not be stable say, over a long period of time due to unexpected internal and or external shocks. However, to filter the exact behavior of a macroeconomic indicator to changes in a predictor variable, a time point in the observable period of economic stability can be use as a base-time point in decomposing the control variable. Unlike situation where dummy variables are representing qualitative data, here, quantitative data is filtered into two indicative predictor variables via the afore-mentioned technique.

The remaining part of the paper is arranged as follows; section 2 deals with the literature review, section 3 deals with the materials and methods, section 4 presents the empirical application, analysis and results and section 5 presents the conclusion and implications.

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**Literature Review**

Models in state-space representation are very few in literature with divergent interest. Carlin et al (1992) studied a Monte Carlo approach to non-normal and nonlinear State- Space modeling. They illustrate the broad applicability of their approach with two examples: a problem involving non-normal error distributions in a linear model setting and a one-step ahead prediction problem in a situation where both the state and observational equations are nonlinear and involve unknown parameters. Jonsen et al (2005) studied a state–space framework that simultaneously deals with errors that are non-Gaussian and vary in time, observations that occur irregularly in time, and complexity in the underlying behavioral processes. They develop a state–space framework that simultaneously deals with these features and demonstrate our method by analyzing three seal pathway data sets. We show how known information regarding error distributions can be used to improve inference of the underlying process(es) and demonstrate that our framework provides a powerful and flexible method for fitting different behavioral models to tracking data.

Bieberle and Gauckler (2002) in their research, a simplified anodic solid oxide fuel cell (SOFC) system, Ni, $H_2$–$H_2O$|YSZ, is investigated using the so-called state-space modeling (SSM) approach that combines experiments, modeling, and simulations. The model is validated by fitting the simulated to the experimental impedance spectra, which were measured under well-defined operating conditions, simulated directly from the assumed electrochemical model and the estimated kinetic constants. Simulations were also carried out varying the triple phase boundary (TPB) length, the partial pressure of hydrogen and of water, and the over potential. A comparison of the simulated with the experimental data proves the feasibility of the approach for investigating the electrochemistry of SOFC anodes. However, it comes out that the assumed model requires modifications. An alternative model is proposed for further investigations. Koirala (2013) investigated the stability of time-varying parameters of the random walk model of inflation in Nepal. Monthly time series of inflation ranging from August, 1997 to July, 2012 has been utilized for the analysis. Applying the Kalman Filter technique for the estimation of coefficients of random walk model, we found non-constant time varying parameters of both the constant and autoregressive of order one AR(1) coefficient of inflation over the long run. The findings do not validate the presumption of stable random walk model of inflation as investigated previously in Nepal.

Amaefula (2017) examined the effects of treasury bill rate(TBR), one-month deposit rate(IMDR), three months deposit rate(IIIMDR), six month deposit rate(VIMDR), twelve months deposit rate(XIIMDR) and prime lending rate(PLR) on inflation in Nigeria. The data sets cover the period of 2006M1 to 2017M4. Ordinary least squares (OLS) and maximum likelihood methods of estimation were applied to the generalized linear models (GLM) specified. The results indicate the following; among all the money market indicators considered, only IIIMDR exacts right directional (negative) effect on inflation, significant at 10% level while XIIMDR and PLR have positive (unexpected directional effect) on inflation, significant at 1% and 5% respectively. TBR at lag 2 exacts right directional (negative) effect on current inflation significant at 1% level. It is observed that among all the predictors considered in this study, three months' deposit rate has direct effect in controlling inflation towards the right direction while treasury bill rate influences inflation toward the right direction in shot-run.

**Material and Methods**

The proposal behind a state-space representation of a complex linear system is to capture the dynamics of an observed (n x 1) vector $Y_t$, in connection to unobserved (r x 1) vector $\varepsilon_t$, known as the state vector for the system. The observed variables are presumed to be related to the state vector through the observation equation of the system. The state-space models consist two kinds of equations: the measurement equation (observed) and state equations (transition).

*Source of Data*

The two data sets on monetary policy rate (MPR) and inflation used to demonstrate the empirical application of this research were obtained from Central Bank of Nigeria (CBN) data and statistics publication 2016 and the data sets cover the period of January, 2007 to May, 2016.

*Model Specification*

$$\begin{aligned} y_t &= \mu_t + \tau_t X_t + \varepsilon_t & \varepsilon_t &\sim \text{NID}(0, \sigma_\varepsilon^2) \\ \mu_{t+1} &= \mu_t + \eta_t & \eta_t &\sim \text{NID}(0, \sigma_\xi^2) \\ \tau_{t+1} &= \tau_t \end{aligned} \tag{1}$$

where $\mu_t$ denotes the unobserved level at time t, $X_t$ is the observed exogenous variable and $t = 1,2,\cdots,n$. The observation and state disturbances $(\varepsilon_t \text{ and } \eta_t)$ are assumed to be serially uncorrelated, normally distributed terms with mean zero (0) and variances $\sigma_\varepsilon^2$ and $\sigma_\xi^2$. The $n \times 1$ observation variable $y_t$ and its development can be branded in terms of an unobserved state vector $\mu_t$ It is assumed here that if $X_t$ has significant influence on $y_t$ then, it should follows that $y_t$ tends to be sensitive to at least one of the indicators variables filtered out using time-base difference procedure. This assumption will be empirically proved using both deterministic and stochastic levels of state space models presented.

*Time-Base difference procedure*

The exogenous variable $X_t$ in the measurement (observed) equation can be decomposed into two indicator variables; $x_{1t}$ (growth indicator) and $x_{2t}$ (drop indicator) using percentage relative change between a base-time observation $\{X_t\}_{t=1}$ and successive observations $\{X_{t+i}\}$ is presented below;

Given a time series observation $\text{X}_\text{t}$ where $t = 1,2,\cdots,n$ and if $t = 1$ is the base-time and $\text{X}_1$ is the base-time observation then, the relative difference between a time series observation at a base-time $\{X_t\}_{t=1}$ and at any successive time point $\{X_{t+i}\}$, $i = 1,2,\cdots,n-1$ is given as

$$\Delta_\text{i} = \frac{|X_1 - X_{t+i}|}{Max(|X_1|,|X_{t+i}|)} = (Max(|X_1|,|X_{t+i}|))^{-1}|X_1 - X_{t+i}| \tag{2}$$

where $i = 1,2,\cdots,n-1$ and $\text{t} = 1,2,\cdots,\text{n}$. Hence, the percentage relative change is given as

$$\delta_\text{i} = \frac{|X_1 - X_{t+i}|}{Max(|X_1|,|X_{t+i}|)} \times 100 = (Max(|X_1|,|X_{t+i}|))^{-1}(|X_1 - X_{t+i}|) \times 100 \tag{3}$$

So, decomposing $X_t$ into two indicator variables $x_{1t}$ (growth indicator) and $x_{2t}$ (drop indicator) using **percentage relative change** between a base-time observation $(X_1)$ and successive observations $(X_{t+i})$, we have

$$x_{1t} = \frac{|X_1 - X_{t+i}|}{X_{t+i}} = \{X_{t+i}\}^{-1}|X_1 - X_{t+i}| \quad \text{, where } \text{i} = 1,2,\cdots,\text{n - 1} \tag{4}$$

$$x_{2t} = \frac{|X_1 - X_{t+i}|}{X_1} = \{X_1\}^{-1}|X_1 - X_{t+i}| \quad \text{, where } \text{i} = 1,2,\cdots,\text{n - 1} \tag{5}$$

The percentage relative change is said to be latent if $(X_1 - X_{t+1}) = 0$. In this case, the base-time observation is strictly equal to the successive observation, hence, $\delta_i = 0$. The vector $\tau_t$ in the observation equation is represented as $\tau_t = \{\alpha_t, \beta_t\}$ and $X_t' = \{x_{1t}, x_{2t}\}$. The coefficients $\alpha_t$ and $\beta_t$ indicate the effects of $x_{1t}$ (growth indicator) and $x_{2t}$ (drop indicator) on $y_t$. In other words, $\alpha_t$ and $\beta_t$ show the sensitivity nature of $y_t$ when $X_t$ rises above or falls below the base-time observation $(X_1)$.

So, rewriting equation (1), we have

$$
\begin{aligned}
y_t &= \mu_t + \alpha_t x_{1t} + \beta_t x_{2t} + \varepsilon_t & \varepsilon_t &\sim \mathrm{NID}(0, \sigma_\varepsilon^2) \\
\mu_{t+1} &= \mu_t + \eta_t & \eta_t &\sim \mathrm{NID}(0, \sigma_\eta^2) \\
\alpha_{t+1} &= \alpha_t \\
\beta_{t+1} &= \beta_t
\end{aligned}
\tag{6}
$$

The deterministic state-space model is obtained by fixing the state disturbance of (6) to zero such that;

$$
\begin{aligned}
\text{for } t = 1; \quad & y_1 = \mu_1 + \alpha_1 x_{11} + \beta_1 x_{12} + \varepsilon_1 \\
& \mu_2 = \mu_1 + \eta_1 = \mu_1 \\
& \alpha_2 = \alpha_1 \\
& \beta_2 = \beta_1 \\
\text{for } t = 2; \quad & y_2 = \mu_2 + \alpha_2 x_{21} + \beta_2 x_{22} + \varepsilon_2 \\
& \mu_3 = \mu_2 + \eta_2 = \mu_2 = \mu_1 \\
& \alpha_3 = \alpha_2 = \alpha_1 \\
& \beta_3 = \beta_2 = \beta_1 \\
\vdots \quad & \qquad \cdots \\
\text{for } t = n \quad & y_n = \mu_n + \alpha_n x_{n1} + \beta_n x_{n2} + \varepsilon_n \\
& \mu_{n+1} = \mu_n + \eta_n = \mu_n = \mu_1 \\
& \alpha_{n+1} = \alpha_n = \alpha_1 \\
& \beta_{n+1} = \beta_n = \beta_1
\end{aligned}
$$

Hence, the deterministic state-space model becomes a classical multiple linear regression model of the form;

$$
y_t = \mu_1 + \alpha_1 x_{t1} + \beta_1 x_{t2} + \varepsilon_t \tag{7}
$$

where $\mu_1$ is the level value and $\alpha_1$, and $\beta_1$ are classical regression coefficients at the beginning of the series and are applied to all t. If the level variable in equation (6) is allowed to vary over time, it becomes a stochastic level.

Rewriting (6) using matrix algebra, and defining the following vectors,

$$a_t = \begin{bmatrix} \mu_{t+1} \\ \alpha_{t+1} \\ \beta_{t+1} \end{bmatrix}, \quad a_{t-1} = \begin{bmatrix} \mu_t \\ \alpha_t \\ \beta_t \end{bmatrix}, \quad \mathrm{Z_t} = \begin{bmatrix} 1 \\ x_{1t} \\ x_{2t} \end{bmatrix}$$

$$T_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad \mathrm{R_t} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

The observation equation is given as (8) and the state or transition equation takes the form of (9) as follows;

$$y_t = Z_t' a_{t-1} + \varepsilon_t \quad , \ \varepsilon_t \sim \mathrm{N}(0, \ H_t) \qquad (8)$$

$$a_t = T_t a_{t-1} + R_t \eta_t \quad \eta_t \sim \mathrm{N}(0, \ Q_t) \qquad (9)$$

Where $y_t$ is a vector observed variable of dimension $n \times 1$, the observation vector $Z_t$ is of $m \times 1$, the transition matrix $T_t$ is of order $m \times m$, $a_t$ is an $m \times 1$ state vector. $R_t$ is simply an identity matrix of order $m \times r$, but in this case, it consists of the first $r$ column of the identity matrix $(r = 1)$. The $R_t$ serves as the selection matrix, because it selects the rows of the state equation which have non-zero disturbances with zero means and unknown variances obtained in an $r \times r$ diagonal matrix $Q_t$.

Defining the following;

$$\phi_t = \begin{bmatrix} T_t \\ Z_t \end{bmatrix}, \quad \nu_t = \begin{bmatrix} R_t \eta_t \\ \varepsilon_t \end{bmatrix}, \quad \mathrm{Q_t} = \sigma_\eta^2 \quad , \quad H_t = \sigma_\varepsilon^2 \quad , \quad \Omega_t = \begin{bmatrix} Q_t & 0 \\ 0 & H_t \end{bmatrix}$$

$$where \ \mathrm{t} = 1,2, \cdots, \mathrm{n}$$

Equation (8) and (9) can be generally rewritten in a compact form as given in (10) below;

$$\begin{bmatrix} a_t \\ y_t \end{bmatrix} = \phi_t a_{t-1} + \nu_t \qquad \nu_t \sim \mathrm{N}(0, \ \Omega_t)$$

(10)

where $\phi_t$ is of dimension $(m+1) \times m$, $\nu_t$ is of dimension $(m+1) \times r$ and $\Omega_t$ is of dimension $(m+1) \times (m+r)$.

*Kalman filter form of estimations*

The Kalman filter consist of two steps; the first step involves forecasting $y_{t+1}$ and $a_{t+1}$ given all information available at time t. The second step consists of updating the forecast of $a_{t+1}$ given observed deviation of $y_{t+1}$ with regards to expected value $y_{t+1/t}$.

*Prediction Step*

$$a_{t+1/t} = T_{t+1} a_{t/t} \qquad (11)$$

$$y_{t+1/t} = Z_{t+1}' a_{t/t} \qquad (12)$$

$$\Sigma_{t+1/t} = E\left( [a_{t+1} - a_{t+1/t}][a_{t+1} - a_{t+1/t}]' \right) = Q_{t+1} + T_{t+1} \Sigma_{t/t} T_{t+1}' \qquad (13)$$

$$\Omega_{t+1/t} \quad = E\left( \left[ y_{t+1} - y_{t+1/t} \right] \left[ y_{t+1} - y_{t+1/t} \right]' \right) = H_{t+1} + Z_{t+1}\Sigma_{t+1/t}Z'_{t+1}$$

(14)

*Updating Steps*

$$a_{t+1/t+1} \quad = a_{t+1/t} + K_{t+1}\left( y_{t+1} - y_{t+1/t} \right) = a_{t+1/t} + K_{t+1}v_{t+1} \qquad (15)$$

$$K_{t+1} = \Sigma_{t+1/t}Z'_{t+1}\left( H_{t+1} + Z_{t+1}\Sigma_{t+1/t}Z'_{t+1} \right)^{-1} = \Sigma_{t+1/t}Z'_{t+1}\Omega^{-1}_{t+1t} \qquad (16)$$

$$\Sigma_{t+1/t+1} = \left( I_d - K_{t+1}Z_{t+1} \right)\Sigma_{t+1/t} \qquad (17)$$

The covariance matrix for the filtering error is givens as

$$\Sigma_{t+1/t+1} = Var\left( a_{t+1} - a_{t+1/t+1} \right)$$

$$= \Sigma_{t+1/t} - \Sigma_{t+1/t}Z'_{t+1}\Omega^{-1}_{t+1/t}\Sigma_{t+1/t} \qquad (18)$$

Matrix $K_t$ is called the Kalman gain matrix and is of order $m \times 1,\ t = 1,2,\cdots,n$. The prediction errors $v_t$ and their variances $\Omega_t$ also plays an important role in the maximization of the log-likelihood function in the state space methods. The diffuse log-likelihood for a univariate state space models is given as

$$\log L(y) = \frac{n}{2}\log\left(2\pi\right) - \frac{1}{2}\sum_{t=d+1}^{n}\log\left(\Omega_t\right) - \frac{1}{2}\sum_{t=d+1}^{n}v_t^2\Omega_t^{-1} \qquad (19)$$

Were d is the number of diffuse initial elements of the state. The value of the log-likelihood function is maximized by simultaneously minimizing the prediction errors $v_t$ and their variances $\Omega_t$.

*State initialization*

The Kalman filter requires initial values for the states and a covariance matrix for the initial states to start off the recursive process. There are several ways of initialization $\left(a_{0/0}, \Sigma_{0/0}\right)$ and these are as follows; Set $\left(a_{0/0}, \Sigma_{0/0}\right)$ to their unconditional values if the value of $\Sigma_{0/0}$ is availably handy; set $a_{0/0}$ to a prior value and take an arbitrary large value for $\Sigma_{0/0}$ if the prior values is not available or uncertain; set a small value for $\Sigma_{0/0}$ if we are sure of the prior value. But according to Koopman et al (1999), unless genuine prior information on $\left(a_1, \Sigma_1\right)$ is available, a diffuse prior with *a=0,* $\Sigma_{\bullet}$ =0 and $\Sigma_\infty = 1$ will be used such that $a_1$ ~$N\left(0,_k I\right)$. Where k is first set to $10^6$ and then multiplied by the maximum diagonal value of the residual covariances to adjust for scale. Hence,

$$k = 10^6 \times \max\left\{ 1\left[ \begin{matrix} Q_t & 0 \\ 0 & \mathrm{H_t} \end{matrix} \right] \right\}$$

(20)

State space estimates the parameters of linear state-space models by maximum likelihood. The Kalman filter is a method for recursively obtaining linear, least-squares forecasts of $y_t$ conditional on past information. These forecasts are used to construct the log likelihood, assuming normality and stationarity. When the model is nonstationary, a diffuse Kalman filter is used.

In order to compare the different estimates of state space models made in this paper, the Akaike Information Criterion (AIC) will be applied:

$$AIC = \frac{1}{n}\left[-2\log L_d + 2(q+w)\right] \qquad (21)$$

where $n$ is the sample size, $\log L_d$ is the value of the diffused log-likelihood function which is maximized in the state space modeling, $q$ is the number of diffused initial values in the state, and $w$ is the total number of disturbance variances estimated in the analysis.

**Empirical Application, Analysis and Results**

Nigeria economy in the recent times has been bedeviled with economic instability due to some external and internal shocks that plunged the economy into experiencing a negative 0.36% growth in the first quarter of 2016. And the consistent sharp rise in monthly core inflation since October, 2015 despite shifts in MPR was more worrisome. Hence, the need for this study and the choice of Nigerian economy for empirical demonstration proposed technique.

In this present research, the sensitivity of inflation to shifts in monetary policy rate (MPR) is examined. Situation could arise where certain internal or external factors could necessitate multiple shifts in the monetary policy rate of a country. For example in Nigeria, prior to the period of global financial crises (GFC) in 2007, the MPR was 10.0%, but before the end of second half of 2007, the MPR has shifted three times, the same happened in 2008. In 2011 alone, the MPR experienced a multiple (6 times) shift, perhaps to recover from the GFC that hit the economy close to recession couple with the persistent inflationary pressure. Despite several attempts by MPC to regulate inflationary pressure via MPR, inflationary pressure in Nigeria has continued to rise, consequently, posing a strong challenge to our economic and financial stability.

According to Emefiele (2016), the Monetary Policy Committee (MPC) met on 23rd and 24th May, 2016 against a backdrop of challenging global and domestic economic and financial conditions and amongst other concerns was a further increase in year-on-year headline inflation to 12.77% and 13.72% in March and April 2016, respectively, from 11.38% in February 2016. The increase in headline inflation in April reflected increases in both food and core components of inflation. Core inflation rose sharply for the third time in a row to 13.35 % in April from 12.17% in March, 11.00% in February and 8.80% in January having stayed at 8.70% for three consecutive months through December, 2015. Food inflation also rose to 13.19 per cent from 12.74 per cent in March, 11.35% in February, 10.64% in January and 10.59% in December, 2015. Though the rising inflationary pressure is attributed to legacy factors including energy crisis reflected in incessant scarcity of refined petroleum products, exchange rate pass through from imported goods, high cost of electricity, high transport cost, reduction in food output, high cost of inputs and low industrial output. And conclusively, the MPC voted to retain the following; MPR at 12.00 %, the Cash Reserve Ratio (CRR) at 22.50 %, the Liquidity Ratio at 30.00 per cent; and the Asymmetric Window at +200 and -500 basis points around the MPR.

In this paper, MPR is used as a control variable which will be decomposed into two indicator variables used to measure the sensitivity of inflation to a rise or drop in MPR. The base-time used is January, 2007 and the value of MPR at that time was 10.00. This period was assumed to be economically more stable with the following reasons; (i) it precede the period of GFC which effected the Nigerian's economy negatively. According to Sanusi(2010) the GFC led to the collapse of many financial institution and even caused an entire nation to be rendered bankrupt In Nigeria, the economy faltered and the banking system experience a crises in 2009, triggered by global event. The stock market collapsed by 70% in 2008-2009. (ii) it is observable from CBN (2008) statistical bulletin that the Nigerian external outstanding debt was lowest since 1991 at about 438.39 billion naira. (iii) the Federal Government domestic debt outstanding which was about 2169.64 billion naira was lowest compared with its increasing value in every successive year. (iv) excange rate was 124.612 naira against one US Dollar and since then, naira has never gained better value than the aforementioned exchange rate. The last and not the least, inflation rate was considerably lower. These and many more justified the choice of the given based year.

*Figure 1: Continuous compounding of inflation rate in Nigeria from 2007M1-2016M5*

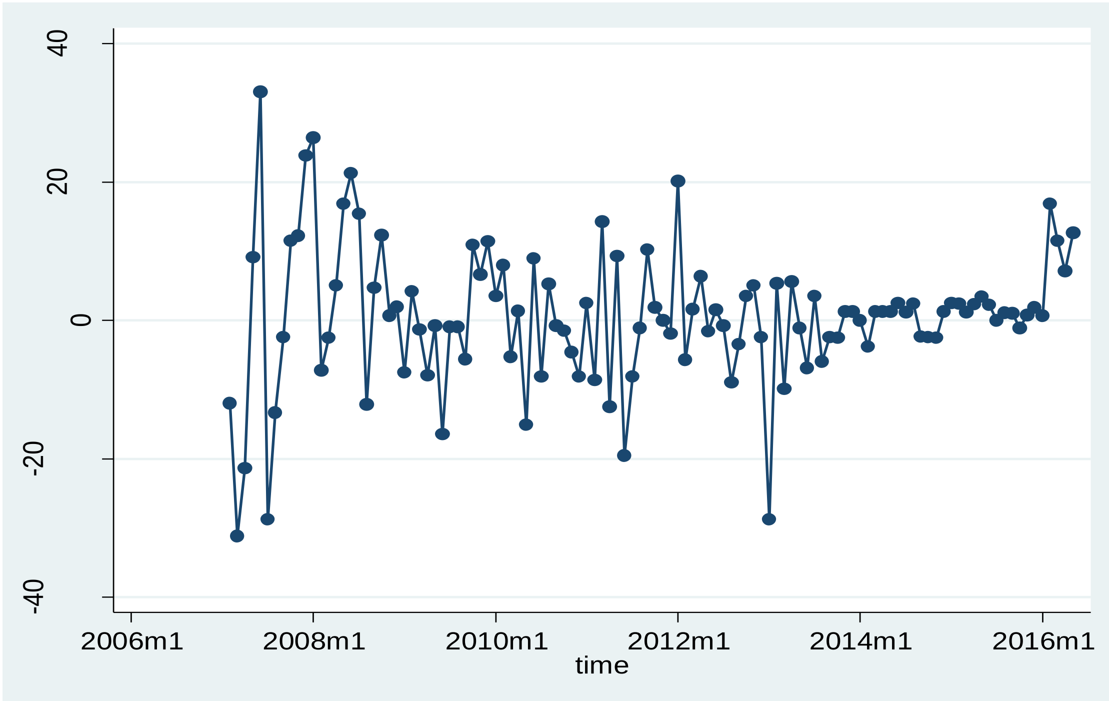



Figure 1 shows large changes in inflation between January, 2007 and August, 2013. Low variation in inflation is observable between September, 2013 and January, 2016 with more concentration around zero.

*Figure 2: Continuous compounding of MPR in Nigeria from 2007M1-2016M5*

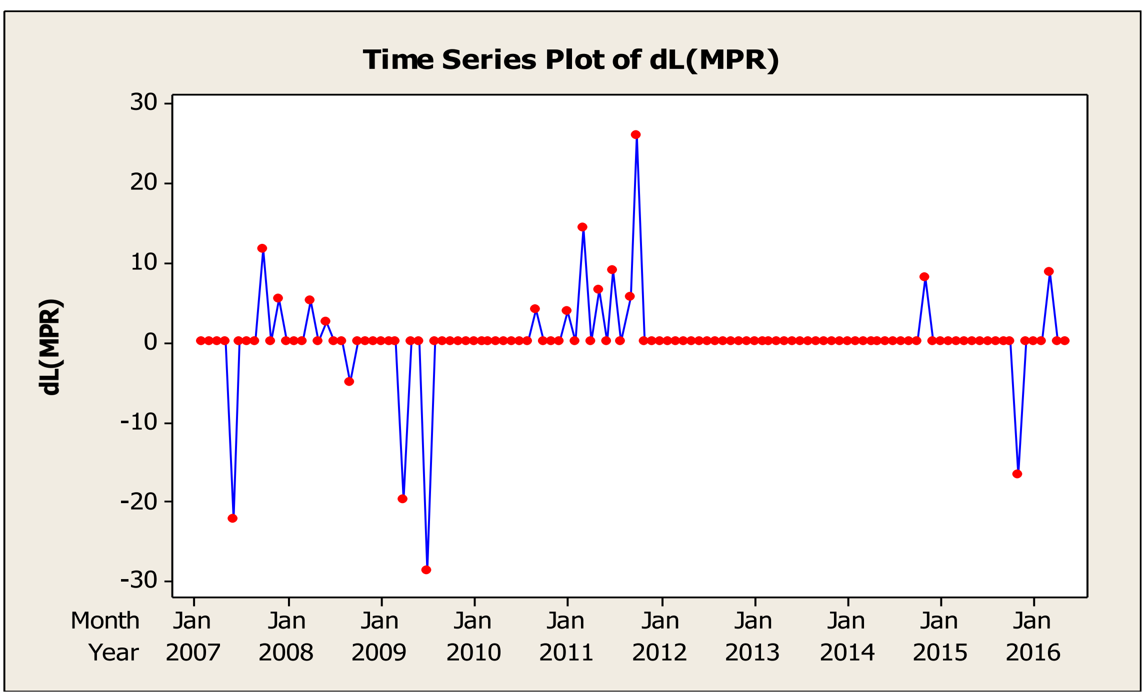


Figure 2 shows continuous compounding of monetary policy rate in Nigeria from January, 2007 to May, 2016. The solid line at zero indicates consistent MPR with few observable shifts (spikes) within the period under investigation.

*Table 1*: *Estimate of state-space model of equation (1)*

| | predictor | Coef. | Std. Err | $z$ | $p>\|z\|$ | 95% conf. interval |
|---|---|---|---|---|---|---|
| $a_t$ | $DL(X_t)$ | -0.4687 | | | | |
| | Const. | 0.3010 | | | | |
| $y_t$ | $DL(X_t)$ | 0.0369 | 0.1732 | 0.21 | 0.831 | -.3026 .3764 |
| | Const. | .5891 | .9583 | 0.61 | 0.539 | -1.2891 2.4674 |

Convergence after 6 iterations; AIC = 7.7829, Number of observation = 112
Wald Chi 2(2) = 0.05 Prob. > Chi 2 = 0.8314, Log likelihood = -418.3398

The result of the above Table 1 shows that the p-value of the z-test is greater than 5% level of significant, revealing that the parameter coefficients model are not significant. The Wald test indicates that the coefficient of the exogenous variable in the observation equation and transition equation is not significant as the p-value 0.8314 is large.

Setting the state disturbance $\eta_t$ in equation (6) to zero, yields the following classical linear regression equation

$$\begin{aligned} &\hat{y}_t = 1.7480 - 0.0651x_1 - 0.0583x_2 + \varepsilon_t \\ &\text{p} > |\text{z}| \quad (0.405) \quad (0.438) \quad (0.675) \\ &LogLikelihood = -418.0485\text{; AIC } = 7.518724 \\ &\text{R-squared } = 0.0056 \end{aligned} \tag{22}$$

*Table 2: Estimate of state-space model of equation (10)*

| | Filtered predictors | Coef. | Std. Err | $z$ | $p>\|z\|$ | 95% conf. interval |
|---|---|---|---|---|---|---|
| $a_t$ | $x_{1t}$ | 0.3521 | | | | |
| | $x_{2t}$ | -0.4664 | | | | |
| | Const. | 0.0711 | | | | |
| $y_t$ | $x_{1t}$ | -0.0651 | 0.0827 | -0.79 | 0.431 | -0.2272 -0.0970 |
| | $x_{2t}$ | -0.0583 | 0.1373 | -0.42 | 0.671 | -0.3274 0.2108 |
| | Const. | 1.7480 | 2.0718 | 0.84 | 0.399 | -2.3125 5.8086 |

Convergence after 7 iterations; AIC=7.52393, Number of observation = 112
Wald Chi 2(2) = 0.63 Prob. > Chi 2 = 0.7300, Log likelihood = -418.04853

The result of the above Table 2 shows that the p-value of the z-test is greater than 5% level of significance, revealing that the parameter coefficients of the filtered predictors in the observation equation are not significant. The Wald test indicates that the joint coefficients of the exogenous variables in the observation equation and transition equation are not significant as the p-value 0.7300 is large.

*Figure 3: Plots of $\varepsilon_t$ Versus $\varepsilon_{t-1}$*

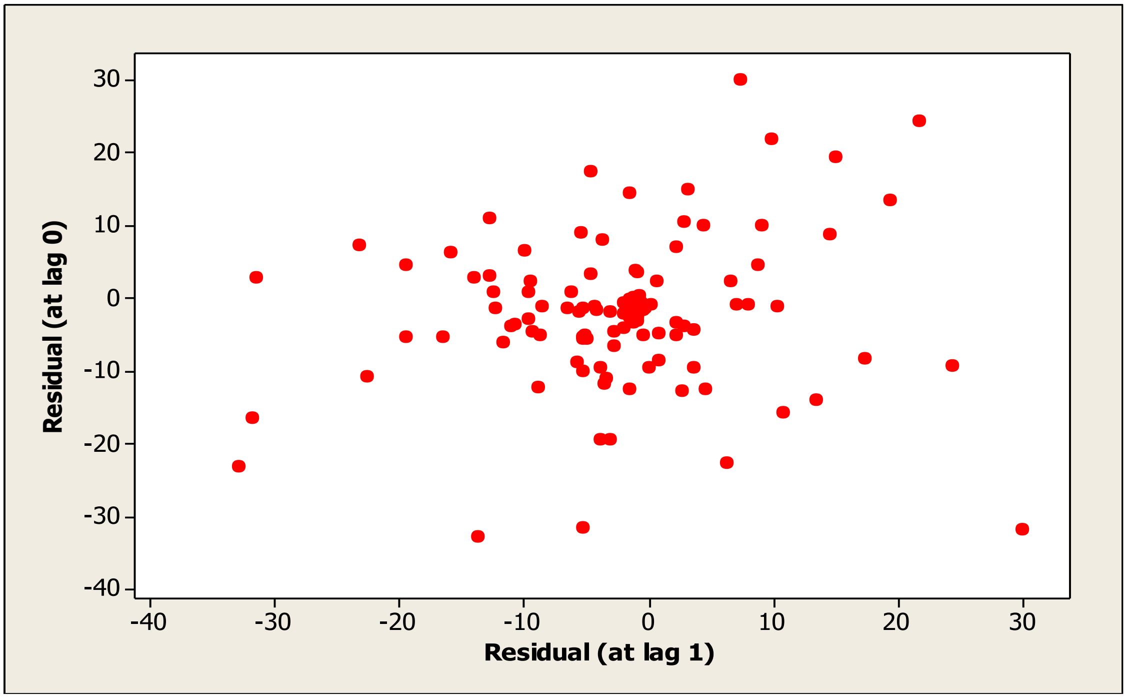
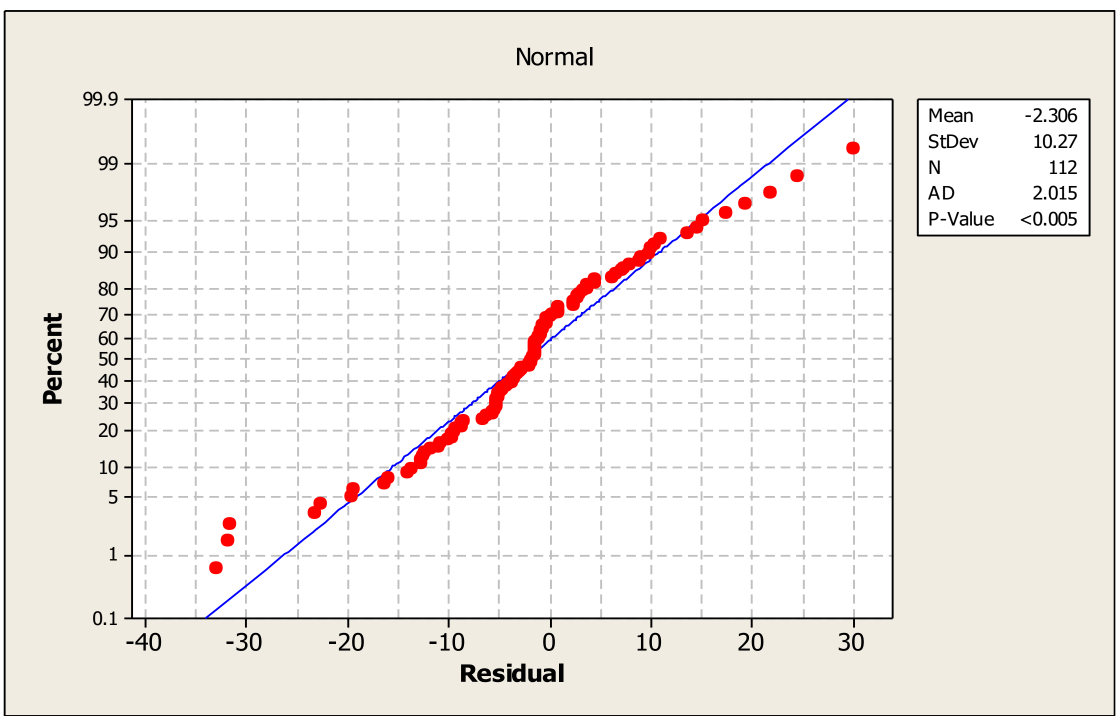



*Figure 4: Probability Plot for the test of normality*



**Discussion of Results**

The result of the state space model of equation (1) as shown in Table 1, indicates that MPR has no significant effect on inflation in Nigeria. In other words, inflation is not sensitive to shifts (changes) in MPR. However, the MPR was filtered into two indicator variables to further study the sensitivity of inflation in Nigeria to MPR (which is used to regulate inflationary pressure), but the results of the deterministic state space model in equation (22) and stochastic state space model in Table2 indicate that inflation is not sensitive to either of the filtered predictor variables. This result has substantiated our prior assumption that if a predictor variable has no significant effect on the dependent variable, neither of the filtered variables via time-based difference will have significant effect on the dependent variable.

Fig.3 shows the plot of $\varepsilon_t$ *versus* $\varepsilon_{t-1}$ used for the test of serial correlation in the error term. A positive serial correlation would produce a scatter of points with a clear positive slope. Since the scatter plot in Fig. 3 does not clearly indicate a positive slope, the assumption of no serial correlation is satisfied. Fig.4 also exhibits the probability plot of the error term in the observation equation. The plot indicates that the normality assumption is also satisfied.

**Conclusion**

The paper examines a state space model framework where the predictor variable in the observation equation is filtered into two indicative predictor variables using time-base difference technique to check the sensitivity of the observed variable $y_t$ to dimensional changes in the predict variable. The Aikaike Information Criterion (AIC) was used to compare the state space with the observed predictor variable $X_t$ and state space model with the filtered predictor variables.

The results showed that the state space models with time base filtered predictor variables are better than the state space model without filtered predictor variables. Our empirical example shows that inflation is not sensitive to our monetary policy rate. The procedure exemplified in this paper can be useful in modeling the behavior of the observed variable to dimensional changes in the predictor (intervention) variable.

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